

Time ordering in the evolution of information processing and modulation systems

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Abstract

The ideas of optimization of learning algorithms in Artificial Neural Networks are reviewed emphasizing generic properties and the online implementations are interpreted from a biological perspective. A simple model of the relevant subsidiary variables needed to improve learning in artificial feedforward networks and the ‘time ordering’ of the appearance of the respective information processing systems is proposed. We discuss the possibility that these results might be relevant in other contexts, not being restricted to the simple models from which they stem. The analysis of a few examples, which range from the lowest cellular scale to the macroscopic level, suggests that similar ideas could be applied to biological systems.

1 Introduction

1.1 Evolution and Optimization

In the study of learning processes in artificial systems, the search for general results can be pursued by concentrating on the statistical mechanics of simple models (Watkin, Rau and Biehl 1993). Rather than being interested in their peculiarities, the aim is to unearth properties that, by recurrently appearing in several of those models, may represent candidates of that sought after generality. The ubiquity of these features may be an indication of their importance in more complex systems, not amenable to an analytical approach, and thus help in suggesting what are the important macroscopic variables in these systems.

The definition of efficiency of an artificial neural network (ANN) depends on the task for which it has been defined. While criteria such as rote memorization, generalization ability or ease of training may be used to label and judge an ANN; adaptiveness, biological plausibility or implementation possibilities can also be relevant parameters. The fact that a given ANN scores well in one or other particular area may be enough to permit its survival as a useful object of study. The construction of new ANN’s from scratch or the evolution to different artificial machines from previous ones, will not be seen as the teleological drive towards the perfect machine, for perfectness is not defined in this multidimensional value space. This evolution leads, instead of a single line or lineage, rather to the construction of a multibranched system.

Not to be thought of as a one dimensional process, this tree or bush can nevertheless be used to define a single lineage process. Starting from the tip of one branch and going backwards through the tree, a trajectory can be distinguished from the neighboring paths that may eventually converge with it as the historical path is retraced. Suppose this backward trajectory is painted in a different color from other separating branches. Now we have an evolution path for which there is at least a pseudo teleological dynamics. Some quality measure, call it \mathcal{Q} can be defined along this path, and as the path is traveled along the forward time direction, then a drive towards better \mathcal{Q} can be identified.

In a competitive environment, the capacity to appropriately deal with and efficiently process information may contribute to give an individual the necessary fitness to be successful. While the build up of better information processing devices is not the generic objective of naturally evolving organisms, it is not totally indefensible that a painted line in a biological evolution tree can be identified where the quantity \mathcal{Q} is, at least loosely, associated with the capacity to deal with information in a certain specific manner. One of the most fundamental information processing capabilities is the extraction of statistical regularities from the environment, i.e. statistical inference, while other such as memory or sensory processing may be thought important inasmuch as they contribute to the former and enhance the organism's predictive capacity.

In the last few years several papers have addressed the problem of determining optimal generalization learning algorithms in ANN (Kinouchi and Caticha 1992, 1993, 1993b, 1996, Biehl and Schwarze 1993, Watkin 1993, Copelli and Caticha 1995, Biehl, Riegler and Stechert 1995, Copelli, Kinouchi and Caticha 1996, Simonetti and Caticha 1996, Van den Broeck and Reimann 1996, Oppen 1996, Oppen and Winther 1996, Copelli *et al* 1997, Winther, Lautrup and Zang 1997) The idea of optimization of learning algorithms, whether applied to on or offline learning, in a supervised or not manner, is based on the fact that a given machine will be expected to perform satisfactorily in a rather restricted environment. Although these algorithms may turn out to be somewhat adaptive¹, it is unreasonable to expect the same algorithm to be optimal under general conditions. However, the specification of a restricted set of environmental variables defines the learning scenario and makes the optimization problem well posed. The learning scenario will define the “evolutionary pressures” which will mold the learning algorithms. \mathcal{Q} is here identified with the generalization ability.

The object of this communication is to deal with the problem of optimization, first by quickly reviewing results obtained in relation to ANN learning from examples and then by giving an interpretation, from a biological point of view, of several features that appear to be characteristic of optimized learning algorithms. This is done in the hope that, if the features reflect properties of learning in general, rather than simply showing effects restricted to the particular chosen scenarios and architectures, then a simple model of the time evolution towards more sophisticated biological information processing can be suggested. The main point we want to stress is that a ‘time’ ordering can be seen to arise in the complexification of the learning algorithms due to the importance of behavioral variables in the efficient modulation of synaptical plasticity.

¹ Tolerance to small changes in the distribution of examples, drift in the underlying rules it tries to infer, or to changing levels of corruption of the data by noise.

1.2 Learning in the presence of Partial Information.

The optimal learner relies on several auxiliary quantities that describe the (joint) probability distribution of examples, that is the learning scenario. In the absence of information on one or more such quantities a full optimization cannot be carried out. Nevertheless, in the presence of partial information (sub)optimal algorithms can be found. Will the inclusion of one more such variable in the ‘information pool’ always lead to an increase in \mathcal{Q} ? Not necessarily, for it may depend on which other variables are available. For example, consider two auxiliary quantities A and B . Let A^- represent that A is missing from the information pool. Appropriate choices, for A and B can be made such that $\mathcal{Q}(A^-, B^-) = \mathcal{Q}(A, B^-) < \mathcal{Q}(A^-, B) < \mathcal{Q}(A, B)$.

We now imagine the steps towards constructing the necessary hardware by some sort of evolution. A new piece of hardware that measures A will not be useful and therefore not included if the necessary hardware to measure B is not yet present. It can be said that B potentiates A as useful information. Evolution can take a path $(A^-, B^-) \rightarrow (A^-, B) \rightarrow (A, B)$, but not $(A^-, B^-) \rightarrow (A, B^-) \rightarrow (A, B)$.

This is what we mean by a ‘time ordering’ in the appearance of the different moduli that measure the several relevant variables. It is an argument for at least time ordering in the built up of functional modularity, but might be useful also for physical modularity development in the presence of some functional localization.

Whether a similar claim holds for the sequential construction of information processing moduli in biological systems evolving under natural selection, is a very interesting but still not clear proposition. We want to present a simple example to show that this, in fact, may be the case.

2 Optimal Learning in a class of ANN

2.1 Modulated Hebbian-like Learning

We review results for a class of feedforward ANN where optimization has been previously studied in the case of supervised learning. It includes the simple perceptron with continuous or binary weights, boolean or linear output, boolean reverse wedge perceptron, tree parity and tree committee machines. For optimal unsupervised learning see (Van den Broeck and Reimann 1996).

The functions ($f : \mathcal{R}^N \Rightarrow \mathcal{R}$ or $\{\pm 1\}$), these machines implement, depend on a set of N parameters or coupling weights $\{J_i\}$ which are inspired by synaptic efficiencies in a biological neural system and are supposed to play a similar role. The object of learning is to modify the set of weights of a student network in order to approximate a function f_0 , unknown except for the information contained in the learning set $\mathcal{L} = \{\mathbf{S}^\mu, \sigma_b^\mu\}_{\mu=1, \dots, P}$, i.e. , the values $\{\sigma_b^\mu\}$ of the function at P instances of the inputs $\{\mathbf{S}^\mu\}$. The outputs $\{\sigma_b^\mu\}$ could even be corrupted by some noise process. Optimization will have, in this work, the aim of maximizing the ability of generalization, i.e. rule inference. While optimal off-line learning has also been studied, we concentrate in what follows in the properties of on-line learning, because of its more biological appeal. We consider the case of single online presentation of examples with no iteration. These conditions are introduced in order to have manageable models from an analytical point of view, but are not responsible for the properties we want to discuss,

which are still present under more general conditions or in other more complex models.

For simplicity we discuss the simplest of all feedforward networks, the single layer boolean perceptron, nevertheless the results are representative of what is found for the other architectures mentioned above. The output σ_h of the perceptron is given by the sign of the post-synaptic field² $h = \mathbf{S} \cdot \mathbf{J} / J$, and the function f_0 it is learning is an ANN of similar architecture, a teacher perceptron with an unknown set of N real weights $\{B_i\}$. We will call $b = \mathbf{S} \cdot \mathbf{B} / B$, the teacher's field. For these machines the generalization error e_g , which measures the probability of disagreement between teacher and student perceptrons is a monotonically decreasing function of the overlap $\rho = \mathbf{J} \cdot \mathbf{B} / JB$, for the perceptron: $e_g = \frac{1}{\pi} \arccos \rho$.

During learning, the presentation of a new example to a network induces a change ΔJ_i in each 'synaptic' weight J_i . We take this change to be of a Hebbian nature in that it is proportional to the intensity of the pre-synaptic input S_i^μ and to the desired output σ_b^μ . This so-called Hebbian term, $\Delta J_i \propto \sigma_b^\mu S_i^\mu$, could in principle be modulated by a series of other processes, increasing or decreasing its importance, in order to enable the system to learn more efficiently. This modulation can be represented by the introduction of a modulation function F , such that now $\Delta J_i \propto F \sigma_b^\mu S_i^\mu$ takes into account other factors of which at this point we have no information.

While *ad hoc* algorithm building, i.e. choosing F , calls for intuition, previous experience and some luck, the constructive nature of the optimization procedure furnishes a set of variables \mathcal{Z} , on which the modulation function depends as well as the function F itself. If optimization is carried under no restrictions, the set \mathcal{Z} will include all the variables which, if known, would contribute to achieve optimal generalization. Several of them, call it the set \mathcal{H} , will not be accessible or 'hidden', while the remaining variables, belonging to \mathcal{V} , are accessible or 'visible'. That is: $\mathcal{Z} = \mathcal{H} \cup \mathcal{V}$. The set \mathcal{V} is the pool of available information referred to in the previous section. Availability conditions may, however, limit the set \mathcal{V} , thereby restricting the learning scenario, leading to suboptimal learning conditions.

We mention what seems to be just a silly technical point, but will be seen to be relevant in section (3). It concerns the presence of the correlation term $\sigma_b^\mu S_i^\mu$ in the change of J_i . One could very well optimize learning algorithms within the class of changes $\Delta J_i = W S_i^\mu$, modulated by an *a priori* unknown function W , obtaining exactly the same results as before. The optimal algorithms work neither by pure correlation nor error correction, they might resemble both types of paradigms in different proportions in different stages of the learning process³.

2.2 The Optimal Modulation Function.

The evolution we want to discuss is restricted to the possible changes in the function F and the set \mathcal{V} , that is to the possible modulation mechanisms and to their overall impact on the generalization ability of systems restricted to Hebbian synaptic modification. The general form of the optimal

² All vectors are written in boldface, e.g. \mathbf{J} , while their lengths, e.g. J are not.

³For the perceptron, at the early stages the algorithm is simple Hebb or pure correlation, while it resembles an error correcting (relaxation) algorithm later on.

modulation function is then

$$F_{\mathcal{H}|\mathcal{V}}^{opt} = J < \frac{b}{\rho} - h >_{\mathcal{H}|\mathcal{V}}$$

proportional to the expectation value of the difference between the fields averaged over the unknown quantities (\mathcal{H}), given the pool of available data (\mathcal{V}). This form holds for the linear, boolean and reverse wedge perceptron as well as related architectures such as the tree parity and committee machines. For fully connected architecture, although optimization has not been totally completed, preliminary results show that the main feature still holds, that is, the modulation functions are still expected values of the form $< \dots >_{\mathcal{H}|\mathcal{V}}$

Learning in the presence of restricted information can be studied by accordingly limiting the set of available variables \mathcal{V} . By starting with an empty \mathcal{V} and sequentially promoting different members from \mathcal{H} to \mathcal{V} several different trajectories in the space of algorithms can be defined. All lead from the simple Hebbian ($F = 1$) to the fully modulated optimal algorithm. An increase in the algorithms' complexity occurs along each trajectory. We can rule out a trajectory to be a product of 'natural evolution' if there is a single step where the performance fails to improve, on the grounds of a cost-benefit argument.

2.3 Common Features of Optimal Modulation Functions

Optimal algorithms, independently of the machine architectures so far studied, share some characteristics.

First of all, the synaptic change depends on the example through the field h ; not only through its sign σ_h ⁴, which determines if the student agrees or not with the teacher on that particular instance; but also through its absolute value, $|h|$. This is used in evaluating the importance of any 'mismatch' between the answer expected by the student and the actual teacher's version. A 'small' $|h|$ may reduce the importance of an error, whereas a 'large' $|h|$ could indicate a particularly important example, with a potentially high value of information. The scale in which 'small' is distinguished from 'large' however is not the same throughout the learning process but can depend on several factors.

The modulation function is time dependent, meaning that the optimal annealing is built into the modulation function. This is better described in terms of performance dependence (Kinouchi and Caticha 1993) rather than time. While the learning of a stationary rule takes place, the generalization error decreases monotonically, and therefore time and performance are interchangeable. However, if the learner has to adapt to a time dependent rule then time duration of the learning process loses importance. Performance though, if and when it can be estimated at all, will still remain of value in determining the amount of effective learning the machine has undergone. It is fundamental to note that the main role of the performance determination, and therefore of the overlap ρ , is in establishing the relevant scale of the field h , and thereby aid in gauging the importance of the 'mismatch' or surprise in having expected a different answer from that of the teacher.

⁴in the case of multilayer (ML) networks, this should read: fields $\{h_i\}$ and total output sign $\sigma(\{h_i\})$

Learning in the presence of noise (Biehl *et al* 1995, Copelli *et al* 1996, Heskes 1994) introduces a host of interesting variations. We will restrict to the case of output or multiplicative noise which is characterized by a single parameter χ , the (independent) probability of a training label being inverted. Under this conditions a new feature sets in and can be dubbed ‘confidence’. The importance of a surprise may be watered down if the teacher is not reliable and there is trade off between surprise and confidence. The cross over from being surprised to not trusting the teacher depends both on the estimated performance and the noise level ⁵ χ .

Of the different features on which the modulation function depends, we now ask: in what order will they appear in a successive construction of the set \mathcal{V} ? The set \mathcal{Z} of relevant variables is determined by unrestricted optimization. For the boolean perceptron we have $\{b, \sigma_b, \xi, h, \sigma_h, \rho, \chi\}$. The teacher internal field b is certainly not available, although in the conditions of supervised learning, its sign σ_b , or at least a noise corrupted version of it, ξ is. The values of the overall internal post-synaptic field h or the student network output σ_h could be used. The average performance or generalization error e_g or the overlap ρ or its estimate may be present. The noise level χ , just an estimate of it (Biehl *et al* 1995) or at least the knowledge of the existence of noise could also be available ⁶.

The suboptimization in the presence of a different set of variables may lead to differential performances. But not always. As one of the most interesting cases, we consider the slightest increase in complexity that a pure unmodulated Hebbian learning algorithm could undergo. The putative improved algorithms can be obtained by finding the optimal modulation functions among the possible $F(h, \sigma_b)$ ⁷, $F(\rho, \sigma_b)$ or still $F(\chi, \sigma_b)$. It turns out that modulating with $F(\Delta)$ leads to an improvement over plain Hebbian ⁸. But the best possible modulation within the class of functions that depend only on e_g or χ is $F = 1$ (!) (Copelli *et al* 1996), i.e. the information they bring is, at this point in the algorithm development process, irrelevant. There is no advantage in developing hardware to measure any of those if the necessary hardware to measure Δ is not already there. The inclusion of the performance e_g leads to an improvement once Δ is available. This translates into an annealed algorithm. At this point, inclusion of the noise level will lead into further improvement of the learning algorithm. The confidence, or lack of it, in the supervised information leads to a possible rejection of outliers. Therefore the performance ordering $\mathcal{Q}(\xi) = \mathcal{Q}(\xi, \rho) < \mathcal{Q}(\xi, h) < \mathcal{Q}(\xi, h, \rho)$ suggests a time ordering for the construction of \mathcal{V} to be $(\xi) \rightarrow (\xi, h) \rightarrow (\xi, h, \rho)$, and not $(\xi) \rightarrow (\xi, \rho) \rightarrow (\xi, h, \rho)$.

The next section will try to make a parallel between these ideas and some biological examples. Before that, we point out the physical meaning of these variables. While $\Delta(< 0) > 0$ signals (dis)agreement of the student with the supervisor, $|\Delta|$ indicates how sure was the student in predicting the answer. A large negative Δ indicates a big, surprising mistake. The capacity of measuring it is tantamount to being able to be surprised, whereas the possibility of modulating learning with

⁵ ‘Confidence’ also appears in the ML case, as different branches can, under optimal conditions, determine which branch ought to be mostly blamed for an overall error or equivalently having the least confidence in its partial answer, even in the absence of noise.

⁶In a more general setting, the distribution of examples should be taken into account, since biases in the inputs will certainly interfere with what student network is considered optimal. Here we will restrict to the case of uniformly, independent, randomly distributed examples.

⁷In this case it depends on the stability $\Delta = h\sigma_b$ or $\Delta = h\xi$ in the presence of noise

⁸That is easy, since several h dependent algorithms can be devised that are nonoptimal improvements over the pure unmodulated Hebbian algorithm.

a Δ depending function implies in the use of the expected vs. actual answer mismatch in learning. The influence of performance on the learning algorithm is done by furnishing the appropriate scale in which surprises are to be judged. A big surprise of an unexperienced learner should not be as important as that of a more advanced student. Neither a big surprise will have the same effect in a gullible student as in one which knows that the incoming information is not completely reliable.

Practical algorithm builders may very well complain that these variables, such as ρ or χ are not available to the student network at all but only certain estimations can at best be made. And in doing so they will discover the main point we want to stress. Optimization methods will determine firstly, the limits of learning and secondly, the possible reliance on some usually hidden quantities in order to attain them. This reliance, rather than hampering the utility of the optimization ideas, is one of its main results. By showing which these variables are, it provides a necessary pressure to develop algorithms or hardware which permit their more efficient determination⁹ This is the most obvious consequence. Whether similar ideas apply to biological evolution is an intriguing thought. Hints that this may be so will be considered in the next section.

3 Some examples drawn from Biology

3.1 Disclaimer

Life in the real world is not as clear cut as in the simple laboratories of the theories reviewed above. In trying to interpret experimental data, a translation of the mathematical language we have employed is necessary. This translation can be done at different hierarchical levels, ranging from the cellular to the behavioral levels.

There is an extensive literature regarding receptive field and synaptic plasticity, (e.g. Cruikshank and Wienberger 1996, Churchland and Sejnowski 1996) and references therein. We certainly can make no attempt at any comprehensive review, but will recall some examples that seem to be natural in the light of previous sections. By selectively choosing only some of those that seem to be on our side we do not wish to imply lack of different mechanisms nor exclude other laws. The critical interpretation of experimental work is left to the experts, and we only use their conclusions. We also claim no final conclusion, only present a set of experimentally backed up hints about the relevance of the previous theoretical results.

3.2 Examples

First of all there is the question about the Hebbian nature of synaptic plasticity or of its extensions, such as the Stent-Hebb law e.g. (Churchland and Sejnowski 1996). The sheer variety of plastic neural circuitry suggests that there very well may be other than just Hebbian-like mechanisms to encode information in the intercellular interactions. Standard Hebbian theories hold that it is the pre-post-synaptical neural activity correlation of activities that governs the change of synaptic efficiencies.

⁹The creation of estimators for the hidden parameters can be viewed as a second order learning process: learning to learn more efficiently (Kinouchi and Caticha 1993, Biehl *et al* 1995, Coehn and Jain 1994)

The necessity as well as sufficiency of Hebbian mechanisms to explain a set of experiments has been satisfactorily established. There is, however, in some other cases evidence for neuromodulated synaptic plasticity which transcends mere correlation mechanisms .

The first example we deal with is the experiment of (Carew, Hawkins, Abrams and Kandel, 1984) as discussed by (Cruikshank and Wienberger 1996). In this experiment in the *Aplysia*, (a) the increase of the synaptic coupling between a pre-synaptic sensory neuron and a post-synaptic motor neuron was induced by correlated activity in both neurons, suggesting a Hebbian mechanism. This was obtained under sensorial stimulation, which caused strong activity of the motor neuron.

To verify sufficiency they tested (b) the effect of simple activity correlation. This was obtained by inducing post-synaptic depolarization, and therefore activity, through the injection of current into the cell, in the absence of external stimulation. Correlation was thus shown insufficient, since alone it did not induce synaptic strengthening. Finally, in experiment (c) its necessity was also discarded by showing an increase in synaptic efficiency in the conditions of the first experiment modified by hyperpolarizing the post-synaptic neuron and thus eliminating the activity correlation.

Without the modulation due to behavioral context no significant plasticity occurs in experiment (b). This would be represented in our ‘modulated Hebbian’ model by a small or absent modulation function F , which could be due to a behavioral feedback. We want to stress the difference between what has been called Hebbian in Physics and Physiology. Physicists have used the desired response σ_b instead of the actual postsynaptic activity σ_J in defining the Hebbian change. This difference is irrelevant for clamped neuron experiments. Synaptic changes, such as the ones described in section 2, proportional to $\delta S_i \sigma_J$, where $\delta = \sigma_J \sigma_b$ have been termed *predictive Hebbian* learning (Montague, Dayan, Person and Sejnowski, 1995).

Another set of experiments (Ahissar *et al.* 1992) deals with the role of behavioral context in the changes of the functional connection (fc) between neurons in the auditory cortex of monkeys. Instead of measuring single synaptic plasticity, they obtained the fc , which is the effective interaction that arises from contributions from all possible pathways between the two neurons, from the Cross Correlation Histograms (CCH) technique. The ratio of the fc after and before the conditioning, which they termed the Strengthening Factor (SF), was plotted against the Contingency Factor (CF), the integrated coactivity (induced gain) during conditioning, obtained from the CCHs, divided by its value before conditioning. Although both in the presence of behavioral relevant context and in its absence, SF and CF were positively correlated, in the former case this relation was much more striking. Their conclusion, that in a behavioral relevant context, coactivity leads to a much higher fc change than when behaviorally irrelevant, is in accordance to what we discussed in section (2).

Among other possible examples, we mention, very briefly, that the influence of surprise in synaptic plasticity in the cerebellum of monkeys, has been reported by Gilbert and Thach (Kandel and Schwartz 1986).

We conclude by mentioning a few facts, very suggestive at the light of what we expounded in the previous sections, that occur, not at the cellular level, but at neuropsychological one. Several works (e.g. Kandel and Schwartz 1986, Shallice 1988) have pointed the amygdala as responsible for identifying the ‘mismatch’ or surprise element in the processing of new information. Work on prefrontal syndrome patients has, on the other hand, indicated the role of the prefrontal lobe in evaluating

performance levels related to working memory ('online') procedures (e.g. Williams and Goldman-Rakic 1996) have been reported to stick to strategies that were once successful (*perseverance* effect) even if its clear, to a normal control, that the underlying rule has changed. Perseverance can be attributed to the lack of feedback from the working memory self-evaluation mechanism.

By excluding different variables in the set \mathcal{V} , different types of lesions can be modeled in a feed-forward net. The degradation of the performance \mathcal{Q} when the self-evaluation module is ineffective shows 'perseverance' effects when learning rules that may change unexpectedly in time. This is in contrast to the adaptive optimal algorithm which detects poor performance and can effectively start relearning once the rule changes. We stress the fact that the optimal perceptron has not been built explicitly to present these perseverance effects when lesioned, but that it is uniquely deduced from the probability distribution associated to the task at hand by the sole requirement of having maximal generalization ability (Kinouchi and Caticha 1993, 1993b) for its particular architecture (see also (Changeux 1992, Levine, Leven and Prueitt 1992)).

On the basis of our earlier remarks it is clear that the surprise measuring hardware is expected to be an *older* structure than the performance measuring hardware. That this 'time ordering' between the amygdala and the prefrontal lobe holds, is well known and therefore may come as no surprise (Kandel and Schwartz 1986). That this is in accord with the theory developed for such simple systems as the feedforward networks here discussed is where we think the real surprise lies. Whether other time ordering sequences can be thus identified will be the subject of future studies.

Finally at an even more macroscopic level, we mention the Rescorla-Wagner model (Rescorla and Wagner 1972, Gluck and Bower 1988, Gluck 1991), widely studied in animal psychology and also used to model human categorization, to support the study of these networks. Mathematically, the Rescorla-Wagner model is a simple perceptron, since decisions are based on weighted sums of signals, learning with an Adaline algorithm. The reason this is sensible is that, although at the microscopic level we have to deal with extremely complex networks, humans frequently use simple algorithms for inference and detection of statistical regularities. There is evidence that humans fail on some nonlinearly separable tasks (Thorpe, O'Reagan and Pouget 1990) of an automatic and non-linguistic nature, suggesting that modeling problem-solving mechanisms by even a simple perceptron may be relevant in these cases. Since the optimal algorithm perceptron takes into account the amount of surprise, stage of learning and a confidence measure in order to learn effectively, we suggest that modeling at macroscopic levels by perceptron architectures can only be ruled out after the inclusion of these properties into the model, otherwise, failure to reproduce experimental results may lie somewhere else and not in the simple network. This work was supported by CNPq and Capes.

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